Measuring Agricultural Financial Conditions: A Mixed-Frequency Dynamic Factor Approach

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Abstract

This study develops a monthly Farm Financial Conditions Index (FFCI) using a mixed-frequency dynamic factor model applied to 127 indicators spanning credit markets, farm income, production costs, asset values, and regional lending conditions. The agricultural sector lacks a comprehensive, continuously updated measure of financial conditions despite recurring episodes of distress that have prompted billions of dollars in emergency government interventions. The index identifies five episodes of sustained departure from neutral conditions between 1989 and 2025, including the early-1990s post-crisis trough, the deepest sample episode, and the 2020–2022 commodity boom, the strongest expansion. Validation against Chapter 12 bankruptcy filings demonstrates a twelve-month lead and unidirectional Granger causality from the index to filings. Subindex analysis reveals a sequential credit channel transmission pattern. Credit supply tightens first, cost pressures emerge next, delinquencies rise with a lag, and asset values adjust last. The index complements existing monitoring efforts by providing a formal aggregation framework that resolves conflicting indicator signals and produces a continuous historical benchmark for comparison.

Keywords: Agricultural Finance, Financial Conditions Index, Mixed-Frequency Data, Dynamic Factor Models, Early Warning

JEL Codes: Q14, C32, C38, G21

1 Introduction

The U.S. agricultural sector accounts for roughly 5 percent of GDP when upstream and downstream linkages are included and carries more than $500 billion in outstanding debt (USDA Economic Research Service, 2026). Agricultural markets have produced recurring financial crises (the post-World War I deflation, the 1980s farm debt crisis, and the post-2013 commodity downturn), each triggering substantial policy responses (Barnett, 2000; Zhang and Tidgren, 2018). These crises arise in part from structural features that distinguish agricultural credit from broader financial systems. Farmland serves as both a productive asset and the primary collateral for agricultural loans, creating feedback mechanisms in which land value changes directly affect borrowing capacity, which in turn influences asset demand and prices (Kiyotaki and Moore, 1997; Kuethe and Hubbs, 2020).

Despite the scale of these policy responses, no comprehensive, continuously updated measure of agricultural financial conditions exists to inform their timing or design, or to support the managerial decisions of agricultural lenders and operators who must allocate capital and risk-management attention against the same conditions. Individual indicators frequently send conflicting signals. For example, machinery markets may signal stress while credit quality appears moderate, and aggregate income may rise while crop-sector producers face losses. Existing monitoring efforts, including indicator-based assessments and expert panels that have demonstrated predictive value, provide timely sectoral readings but lack a formal aggregation framework that resolves these conflicts into a single, continuously updated signal with a historical baseline (Gustafson, 1989; Ifft et al., 2026).

This institutional gap raises three questions that motivate the present paper. First, can a single common factor extracted from a large, mixed-frequency panel of agricultural financial indicators provide a continuously updated, internally consistent measure of farm financial conditions? Second, does decomposing such an index by indicator category convey economically meaningful information about the *source* of emerging stress, information that both policy responses and managerial decisions must distinguish? Third, does the resulting index carry leading content for severe farm financial distress, as measured by Chapter 12 bankruptcy filings, and what does the timing of that lead imply for the design of early intervention?

We address these questions by constructing a monthly Farm Financial Conditions Index (FFCI), which extracts a single common factor from 127 indicators spanning credit markets, farm income, production costs, asset values, and regional lending conditions, observed at monthly, quarterly, and annual frequencies. The mixed-frequency dynamic factor model, estimated via the expectation-maximization (EM) algorithm (Shumway and Stoffer, 1982; Doz et al., 2012), preserves the timing information in each indicator and produces a continuously updated index from 1989 to the present. Beyond the headline measure, the framework decomposes contributions by theory-defined indicator category, identifying whether emerging stress originates in credit markets, commodity prices, or farm balance sheets.

Our answers to these questions constitute the paper's three contributions. First, the paper

constructs the first mixed-frequency financial conditions index for the U.S. agricultural sector, extending the factor model framework established by the Chicago Fed's NFCI (Brave and Butters, 2011) and the Kansas City Financial Stress Index (Hakkio et al., 2009) to a sector that has lacked a comparable monitoring tool despite its scale and policy significance.

Second, validation against Chapter 12 farm bankruptcy filings, a revealed-preference indicator of severe farm financial distress, establishes the index's predictive content. The FFCI leads filings by approximately one year, with Granger causality (Granger, 1969) running from conditions to filings but not the reverse. Subindex analysis reveals a sequential transmission pattern in which credit supply leads, cost and delinquency pressures follow at intermediate lags, and asset values adjust last. This ordering, consistent with the credit channel transmission predicted by the conceptual framework developed in Section 3, provides a staging framework for early warning and targeted intervention.

Third, the decomposition by indicator category identifies not just whether conditions are deteriorating but *why*. By separating contributions from income, expenses, credit stress, credit supply, and asset values, the framework distinguishes among the channels driving sectoral conditions at any point in time. This distinction is directly relevant to policy design, where the appropriate response, whether income support, liquidity intervention, or broad-based stabilization, depends on the originating channel. It is equally relevant to agricultural lenders and operators, who must allocate risk-management attention across channels rather than to a single headline number.

The remainder of the paper is organized as follows. Section 2 reviews the agricultural finance literature and existing approaches to measuring farm financial conditions. Section 3 develops the conceptual framework. Section 4 describes the data. Section 5 presents the methodology. Section 6 reports the empirical results and validation. Section 7 discusses the findings. Section 8 concludes.

2 Literature Review

Barnett (2000) documents that early warning signs of the 1980s farm financial crisis were visible by the late 1970s, with farm income falling 25 percent below the 1970–1974 average in real terms and the American Agriculture Movement protests of 1977–1978, yet the policy response did not arrive until mass foreclosures were underway. Boehlje et al. (2011) place the 1980s episode within a longer historical pattern of recurring agricultural boom-bust cycles driven by export shocks, commodity price spikes, low interest rates, and debt accumulation, with similar dynamics evident across the 1910s, 1940s, and 1970s booms. Agricultural economists have long recognized this diagnostic challenge. Gustafson (1989) identified the fundamental difficulty of synthesizing contradictory financial indicators for agricultural credit evaluation. Burns et al. (2015) note that "financial stress is a latent variable which is imperfectly measured by financial ratios and credit rating models," a point first formalized by Shonkwiler and Moss (1993), who observed that "no one financial measure can unambiguously determine financial stress." Empirical evidence supports this view. Using the 1985 USDA Farm Costs and Returns Survey, Jolly et al. (1985) document that 75 percent of

operators with negative cash flows had debt-to-asset ratios below 40 percent and that nearly half of operators with low debt-to-asset ratios nevertheless had negative cash flow, direct evidence that no single balance-sheet or income measure consistently identifies stress.

The agricultural finance literature has established a rich set of indicators that reflect different dimensions of sectoral financial health. Calomiris et al. (1986) provide a theoretical decomposition of farm financial conditions into four channels: the interest rate channel (cost of borrowing), the collateral channel (land values and borrowing capacity), the debt service channel (cash flow adequacy), and the bank failure channel (disruption of lending relationships through institutional stress). Each channel operates through distinct mechanisms and can send signals that diverge at any given time. The conceptual framework developed in Section 3 adapts this decomposition into five empirically distinguishable indicator categories for measurement purposes.

Prior efforts to measure agricultural financial conditions empirically have relied on indicator-based frameworks rather than formal aggregation. Key et al. (2019) track sectoral-level indicators including net cash farm income, farm sector debt, interest expenses, farmland values, and the debt-to-asset ratio, alongside farm-level measures from the Agricultural Resource Management Survey such as the term debt coverage ratio and leverage classifications. This indicator-based tradition extends an approach pioneered during the 1980s farm debt crisis by Jolly et al. (1985), who combined debt-to-asset ratios, cash flow, and return on equity in a national assessment that documented stress incidence, intensity, and duration. Burns et al. (2015) organize farm-level financial health into four categories (favorable, marginal income, marginal solvency, and vulnerable) using thresholds on net farm income and the debt-to-asset ratio established by the Farm Financial Standards Council. Giri et al. (2024) extend this framework with 16 financial ratios spanning profitability, liquidity, solvency, efficiency, and repayment capacity, finding that in 2020, 16 of 19 ratios were weaker than their 2000–2019 averages despite apparently healthy aggregate balance sheets, a deterioration masked by government transfers and unrealized capital gains on farmland.

Credit market indicators capture a distinct dimension of financial conditions, reflecting the price and quantity of credit access. Loan delinquency rates from commercial bank call reports, Farm Credit System performance data, and Federal Reserve district agricultural credit surveys capture the progression from early payment difficulties to severe distress (Dinterman et al., 2018). Kuethe and Hubbs (2020) examine cyclical fluctuations in real growth rates of farm real estate prices, farm sector debt, and leverage from 1960 to 2018 and find that the agricultural credit cycle is slightly countercyclical to the broader economic cycle. The institutional reforms enacted following the 1980s farm financial crisis (Farm Credit System recapitalization, Chapter 12 bankruptcy, and the Disaster Assistance and Debt Set-Aside Programs) appear to have moderated subsequent cycles, with the early-2000s upturn substantially more subdued than the 1980s buildup. They demonstrate that the agricultural credit cycle serves as an early warning indicator of farm loan delinquencies and farm bankruptcies, with credit cycle peaks leading distress measures by multiple years. The FFCI panel constructed in this paper incorporates 78 such credit indicators, including delinquency rates from Call Reports, Federal Reserve district survey measures, and Terms of Lending Survey

data (Section 4).

The asset market channel operates with distinctive dynamics in agriculture. Farmland constitutes most farm sector assets and serves as the primary collateral base for agricultural lending (Barry, 1995; Kiyotaki and Moore, 1997; USDA Economic Research Service, 2026), creating feedback mechanisms between land values and borrowing capacity. Evidence from recent agricultural downturns confirms the importance of this channel. Farmland values can remain firm even as crop revenues decline, creating a divergence between cash-flow-based and asset-based measures of financial health that complicates assessment (Kauffman and Clark, 2017; Zhang and Tidgren, 2018). Because farmland values both reflect and shape the collateral position of agricultural borrowers, their drivers–expected returns to land, alternative-use values, interest rates, and macroeconomic conditions–are central to how lenders evaluate creditworthiness and how operators access capital. Briggeman et al. (2009) document this lender-side mechanism directly, finding that agricultural land values Granger-cause net loan charge-offs at agricultural banks with multi-year leads, and that the same dynamic operates at the Farm Credit System.

Individual indicators often send conflicting signals about farm financial conditions. The post-2013 downturn, in particular, illustrates this. Farm incomes declined by nearly 50 percent from their peak while farmland values remained elevated, credit surveys indicated tightening but delinquency rates had not spiked, and farmer sentiment diverged sharply depending on whether current conditions or future expectations were being measured (Zhang and Tidgren, 2018; Ifft et al., 2026).

The post-2020–2022 cycle exhibits the same divergence pattern. Machinery market indicators have signaled elevated stress, with equipment sales materially below prior-year levels, while credit quality indicators have suggested only moderate risk (Ifft et al., 2026). Average net cash farm income has been forecast to increase modestly even as corn and cotton operations face material income declines (Langemeier and Colussi, 2026). Roughly a third of farmers carry unpaid operating debt from prior years, a substantial increase relative to earlier in the decade (Langemeier and Colussi, 2026). Practitioners describe the current situation as a "check engine light" that is beginning to flash, with the farm sector's reliance on government payments at its highest share since 2008 (Kohl, 2026).

The difficulty of reconciling these signals has motivated several recent initiatives. Ifft et al. (2026) compile a quarterly dashboard of fourteen quantitative indicators across four dimensions of farm financial health (farmer and banker sentiment, farm income and balance sheet health, machinery market dynamics, and credit quality), interpreted by a panel of agricultural economists who provide risk and momentum assessments. The Rural and Farm Finance Policy Analysis Center has developed an Early Warning System that convenes state-level expert committees to contextualize national and regional data with local conditions assessment (Rural and Farm Finance Policy Analysis Center, 2026). These efforts provide timely, expert-informed monitoring. However, they share a limitation: the absence of a formal aggregation framework that synthesizes conflicting signals into a single, continuously updated measure with a historical baseline for comparison.

The idea of using latent variable methods to measure agricultural financial conditions is not

new. Shonkwiler and Moss (1993) constructed a single latent stress index using confirmatory factor analysis on four annual indicators spanning 1914–1988, demonstrating that the approach could identify and compare major stress episodes across decades. Their approach was limited to four variables observed annually and used a static model without dynamics. The sample ended in 1988 and could not be extended in real time, leaving three subsequent crises (2008, the 2014–2016 agricultural downturn, and the 2023–2024 deterioration) outside the measurement window.

In the broader financial system, composite financial conditions indices have become standard tools for real-time monitoring and policy evaluation. These indices demonstrate that synthesizing large indicator sets through factor models produces decomposable, historically comparable measures that integrate conflicting signals into a single output. The Chicago Fed's National Financial Conditions Index applies a dynamic factor model to over 100 indicators spanning money markets, debt and equity markets, and the banking system (Brave and Butters, 2011), and the Federal Reserve Banks of Kansas City (Hakkio et al., 2009) and Cleveland (Manamperi, 2015) have constructed similar indices. The empirical relevance of these indices for forecasting macroeconomic risk is well-established. Adrian et al. (2019) show that the NFCI is the dominant predictor of the lower tail of the conditional distribution of U.S. GDP growth, with downside risk accounting for nearly all of the time variation in growth volatility. No equivalent index exists for the agricultural sector. The macro-financial indices contain no agriculture-specific indicators, and the assumption that broad money-market and banking conditions adequately summarize sectoral conditions fails when, as in agriculture, the sector exhibits idiosyncratic credit dynamics only weakly correlated with broader business cycles (Kuethe and Hubbs, 2020).

3 Conceptual Framework

Agricultural Financial Conditions as a Latent Variable

We define agricultural financial conditions as the aggregate state of credit availability, asset values, income generation, and balance sheet health that determines the sector's ability to finance ongoing production and absorb shocks. This state is not directly observable. Any single indicator, net cash income, farmland values, delinquency rates, or loan volumes, captures only one dimension, and as discussed in Section 2, individual indicators routinely send conflicting signals about the underlying conditions. The framework adopted here treats conditions as an unobserved process f_t that is reflected, with noise, in a large set of observable indicators $\{y_{1,t}, \ldots, y_{N,t}\}$ spanning the channels through which the financial system operates:

$$y_{i,t} = g_i(f_t) + \epsilon_{i,t}, \quad i = 1, \ldots, N. \tag{1}$$

Each indicator carries information about f_t filtered through a series-specific mapping $g_i(\cdot)$, with an additive idiosyncratic term $\epsilon_{i,t}$ that absorbs series-specific variation, measurement error, and dimensions of conditions not shared with the common state. The measurement task is to recover

f_t from the observed indicators while accounting for the heterogeneous noise structure.

This places agricultural conditions measurement in the same class as the financial conditions indices developed for the broader economy by Brave and Butters (2011) and Hakkio et al. (2009) and the macro-financial latent-factor models of Stock and Watson (2002) and Doz et al. (2012). The contribution is not the framework itself but its application to a sector for which no such measure exists, together with the specification of the channels through which agricultural financial conditions operate.

Channels of Transmission

The literature on agricultural credit identifies four interrelated channels through which financial conditions affect farm operations (Calomiris et al., 1986; Barry, 1995; Kuethe and Hubbs, 2020; Kiyotaki and Moore, 1997). Each channel produces observable indicators with distinctive theoretical properties, and the framework treats them as the constituent dimensions of f_t.

The *income channel* reflects cash flow adequacy through gross receipts from crop and livestock sales, government payments, and net farm income. Improved agricultural conditions increase income and strengthen debt-service capacity, while worsening conditions reduce income and make it harder to meet financial obligations. Additionally, income indicators show a positive correlation with the variable f_t. Government payments have become a substantial structural component of U.S. farm income. Goodwin and Mishra (2006) document their effects on farm balance sheets and production decisions, finding that direct decoupled payments produce small but statistically significant acreage responses for the major Corn Belt crops.

The *expense channel* captures the input-cost burden: prices paid for fertilizer, fuel, feed, labor, and equipment. The sign of this channel's relationship to f_t is theoretically ambiguous. Rising input prices increase production costs, which can compress margins and indicate stress; but input prices also rise during periods of high agricultural activity and strong demand, in which case they signal expansion rather than distress. The covariance structure of the data, rather than ex ante restrictions, determines which interpretation dominates.

The *asset value and collateral channel* captures the role of farmland and other productive assets in both the production process and the lending relationship. Farmland constitutes approximately 80 percent of total farm sector assets and serves as the primary collateral base for agricultural loans (Barry, 1995). Through the financial accelerator mechanism formalized by Kiyotaki and Moore (1997) and Bernanke et al. (1999), asset values both reflect and amplify financial conditions: rising land values relax collateral constraints and expand borrowing capacity, which raises asset demand and prices further; falling values do the reverse. Asset indicators co-move positively with f_t, but adjust slowly due to the institutional and informational frictions in farmland markets.

The *credit channel* captures the interface between farmers and lenders, and it is useful to separate two dimensions. *Credit stress indicators* measure observable distress at this interface: delinquency rates, charge-off rates, nonaccrual loan shares, and the effective interest rates borrowers face. These rise when conditions deteriorate and co-move negatively with f_t. *Credit supply*

indicators measure institutional capacity and willingness to lend: loan volumes, fund availability, collateral requirements, and average maturities. These contract when banks pull back from agricultural lending and expand when capacity grows, co-moving positively with f_t. The empirical distinction between these two credit dimensions, motivated by the theoretical separation between the price and quantity of credit identified by Calomiris et al. (1986), becomes important for early warning: the two dimensions adjust at different speeds, with supply typically responding before observable stress emerges.

The four-channel framework implies many indicators but does not, in itself, imply a single common factor. Each channel could in principle evolve independently of the others, generating a vector-valued state $\mathbf{f}_t$ rather than a scalar. The single-factor specification reflects a theoretical claim worth stating explicitly: agricultural financial conditions, properly defined, should co-move because the channels are linked.

Income shortfalls deplete reserves and stress balance sheets, raising delinquencies and impairing collateral; declining asset values tighten borrowing capacity, constraining the ability to finance operations and pressuring income; credit tightening forces deleveraging, further weakening balance sheets. These feedback mechanisms, formalized for the broader economy by Kiyotaki and Moore (1997) and Bernanke et al. (1999) and documented for agriculture by Kuethe and Hubbs (2020) and Calomiris et al. (1986), predict that broad sectoral conditions move together over the medium term even when short-run divergences arise. A single latent factor representing this co-movement captures the systematic component of agricultural financial conditions; channel-specific deviations and series-specific noise are absorbed into the idiosyncratic component of Equation (1).

This theoretical position is open to empirical refutation. If the data require multiple factors to explain a substantial share of common variation, the single-factor specification would fail, and the framework would need to admit channel-specific dynamics. Section 5 reports the factor-selection tests that bear on this question.

The conceptual framework generates four predictions that the empirical analysis can test. First, the indicator categories should load on the common factor with signs consistent with the theoretical channel descriptions: income, asset values, and credit supply positively; credit stress negatively; expenses ambiguously, with the sign determined empirically. Second, the data should admit a single dominant factor, consistent with the integrated nature of the channels. Third, the channels should not move synchronously: the financial-accelerator mechanism predicts that credit supply adjusts before observable stress and that asset values respond last. Fourth, the latent factor should lead severe financial distress, because the institutional response to deteriorating conditions (default, restructuring, bankruptcy) follows the conditions themselves with substantial delay. Each prediction is taken up in Section 6.

4 Data

The FFCI draws on 127 time series from six primary sources. These are the Federal Reserve Board's Call Reports and Terms of Lending Survey, Federal Reserve district agricultural credit surveys (Chicago, Kansas City, Dallas, Minneapolis, and St. Louis), USDA National Agricultural Statistics Service price indices, USDA Economic Research Service farm income and wealth statistics, and macroeconomic aggregates from the Federal Reserve Economic Data (FRED) repository maintained by the Federal Reserve Bank of St. Louis. The dataset spans January 1989 through January 2026, with individual series start dates varying by source availability. Table 1 summarizes the composition by category and frequency.

The indicator set is organized around the five channels developed in the conceptual framework (Section 3). These are Income, Expenses, Asset Values & Leverage, Credit Stress, and Credit Supply. *Income* (12 series) includes monthly NASS prices received for crops, livestock, and all commodities; quarterly Federal Reserve district survey diffusion indices of farm income; and annual USDA ERS measures of net cash income, crop and livestock receipts, and government payments. *Expenses* (15 series) tracks monthly NASS prices paid for fertilizer, feed, fuel, labor, machinery, and building materials, alongside annual total production expenses and agricultural employment. *Asset Values and Leverage* (22 series) monitors quarterly district survey farmland values, USDA annual balance sheet items, and Call Report banking performance ratios (equity ratio, loan-to-deposit ratio, net interest margin, return on assets). *Credit Stress* (41 series) captures the price dimension of agricultural credit: delinquency and nonaccrual rates from Call Reports, effective interest rates and floating rate shares from the Terms of Lending Survey, and district survey measures of collateral requirements, loan renewals, and repayment rates. These series measure conditions that worsen when borrowers face financial difficulty. *Credit Supply* (37 series) captures the quantity dimension: loan volumes and counts from Call Reports and the Terms of Lending Survey, average loan sizes and maturities, and district survey measures of fund availability and loan demand. The distinction between Credit Stress and Credit Supply follows Calomiris's separation of price and quantity mechanisms in credit markets (Calomiris et al., 1986). Credit Stress captures the *price* dimension, including the rates and fees borrowers face and the rates of nonperformance lenders experience, and these indicators worsen during financial distress. Credit Supply captures the *quantity* dimension, including loan volumes, fund availability, and lending terms set by institutions, and these indicators contract when lenders pull back, even before stress becomes observable in delinquency data. The two dimensions move at different speeds during stress episodes, with quantity often adjusting before price, a sequence we confirm empirically in Section 6.

Credit indicators together account for 61 percent of the panel (78 of 127 series). This reflects both the richness of available data (five Federal Reserve Districts publish quarterly agricultural credit surveys, and Call Reports provide granular loan performance data by type and severity) and the theoretical importance of credit channels in agricultural financial conditions (Kuethe and Hubbs, 2020). The count imbalance does not mechanically dominate the index. The factor model

assigns weights (loadings) based on covariance with the common factor, not series count.

The mixed-frequency structure is central to the index's design. Monthly is the highest frequency the FFCI uses, even though daily and weekly commodity prices are available. The index is intended to measure financial conditions that evolve at the monthly-and-slower rhythm of farm income, balance sheet, and lending decisions, and higher-frequency price noise would not add information at the relevant timescale. Monthly commodity prices and employment indicators (14 series) provide the most timely signals. Quarterly credit surveys and lending data (106 series) capture financial system dynamics at an intermediate lag. Annual balance sheet data (7 series) anchor structural assessments of sector solvency. The state-space framework described in Section 5 synthesizes these signals at monthly frequency through the Kalman filter.

All series undergo stationarity transformations guided by Augmented Dickey-Fuller tests, including log first differences, first differences, and levels depending on time-series properties. After transformation, we standardize series to zero mean and unit variance. The Kalman filter naturally handles the unbalanced panel structure and missing observations. Complete metadata for all 127 series, including transformations, sample windows, and source documentation, appears in Table A.1.

Table 1: Indicator panel composition.

Category	N	**Monthly**	**Quarterly**	**Annual**
Income	12	3	5	4
Expenses	15	11	3	1
Asset Values & Leverage	22	0	20	2
Credit Stress	41	0	41	0
Credit Supply	37	0	37	0
Total	127	14	106	7

Notes: The Farm Financial Conditions Index (FFCI) draws on 127 indicators from Federal Reserve Board Call Reports and Terms of Lending Survey, Federal Reserve district agricultural credit surveys (Chicago, Kansas City, Dallas, Minneapolis, and St. Louis), USDA National Agricultural Statistics Service price indices, USDA Economic Research Service farm income and wealth statistics, and Federal Reserve Economic Data (FRED) macroeconomic aggregates. The sample spans January 1989 through January 2026, with individual series start dates varying by source availability. N denotes the number of indicators in each category. Categories follow the five-channel conceptual framework developed in Section 3. Complete metadata for all 127 series, including transformations, sample windows, and source documentation, appears in Table A.1.

5 Methodology

This section presents the empirical model used to extract the latent factor f_t defined in Section 3. The contribution is the synthesis of three components into a single coherent framework: a mixed-frequency state-space representation following Mariano and Murasawa (2003) and Aruoba et al. (2009) that accommodates monthly, quarterly, and annual indicators within a monthly factor; EM estimation following Shumway and Stoffer (1982), Doz et al. (2012), and Bańbura and Modugno

(2014) that handles the 383-parameter problem and the unbalanced mixed-frequency panel without numerical gradients; and a free-loading specification that allows the covariance structure of the data, rather than ex ante restrictions, to determine the sign of each indicator's relationship to the common factor. The third component is essential for this application. Of the 127 indicators, 78 are credit measures whose theoretical sign is ambiguous, as discussed in Section 3. Rising interest rates may signal stress or strength; rising loan volumes may signal credit tightening or expansion. A measurement framework that imposed signs ex ante would foreclose the empirical identification of the credit channels developed in Section 3.

Mixed-Frequency Dynamic Factor Model

We extract a single common factor from the 127-indicator panel using a dynamic factor model in state-space form. The choice of a single factor is supported by the eigenvalue ratio test of Ahn and Horenstein (2013), which selects $r = 1$ with a first-to-second eigenvalue ratio of 10.8 (the first principal component explains 53 percent of total cross-sectional variance). The Online Appendix, available upon request from the authors, documents the full set of factor selection tests.

The measurement equation relates each transformed, standardized indicator to the latent monthly factor:

$$y_{i,t} = \lambda_i f_t + \epsilon_{i,t}, \quad i = 1, \ldots, N = 127 \tag{2}$$

where f_t is the common factor capturing agricultural financial conditions, λ_i is the factor loading measuring indicator i's sensitivity to the common factor, and $\epsilon_{i,t}$ is an idiosyncratic error. Each idiosyncratic component follows an independent AR(1) process:

$$\epsilon_{i,t} = \rho_i \epsilon_{i,t-1} + u_{i,t}, \quad u_{i,t} \sim N(0, \sigma^2_{u_i}) \tag{3}$$

This specification captures series-specific persistence (for example, the institutional smoothing in bank Call Report data or the slow adjustment of farmland values), preventing it from being attributed to the common factor.

The factor follows an AR(2) process, selected by the Bayesian and Hannan–Quinn information criteria from specifications of order one through four:[1]

$$f_t = \phi_1 f_{t-1} + \phi_2 f_{t-2} + \eta_t, \quad \eta_t \sim N(0, 1) \tag{4}$$

Mixed-Frequency Temporal Aggregation

Indicators observed at quarterly and annual frequencies relate to temporal aggregates of the underlying monthly factor. *Flow* variables (measured over a period, such as quarterly farm income or annual government payments) aggregate as averages. A quarterly flow indicator reflects the three-month average $\frac{1}{3}(f_t + f_{t-1} + f_{t-2})$. *Stock* variables (measured at a point in time, such as

[1] Full lag selection results are reported in the Online Appendix.

farmland values or end-of-quarter loan balances) relate to the end-of-period value f_t. Annual indicators aggregate analogously over twelve months. These relationships are implemented through time-varying measurement matrices in the state-space representation following Mariano and Murasawa (2003), with lower-frequency series treated as monthly indicators with systematically missing observations following Bańbura and Modugno (2014); the same state-space dynamic-factor framework, at daily base frequency, underlies the Aruoba–Diebold–Scotti business conditions index for the macro-economy (Aruoba et al., 2009). The state vector $\boldsymbol{\alpha}_t$ contains twelve lags of the factor to accommodate annual temporal aggregation, plus the 127 idiosyncratic states when all AR(1) processes are active, yielding a total of 383 free parameters.[2]

Identification

Dynamic factor models with unrestricted loadings exhibit rotational indeterminacy. Replacing f_t with $c \cdot f_t$ and each λ_i with λ_i/c for any $c \neq 0$ preserves the measurement equation $y_{i,t} = \lambda_i f_t + \epsilon_{i,t}$, leaving scale unidentified. Setting $c = -1$ reverses the sign of f_t and of all loadings simultaneously, leaving the sign unidentified. We impose two normalizations to resolve this indeterminacy.

Scale. The factor innovation variance (the variance of η_t in Equation 4, representing the period-to-period shock to the factor) is fixed at $\sigma_\eta^2 = 1$ throughout estimation. This identifies the latent factor scale in standardized units. Under this normalization, an estimated loading $\hat{\lambda}_i$ represents the expected change in indicator i associated with a one-standard-deviation innovation to the factor. We adopt this approach rather than fixing a specific loading (for instance, $\lambda_1 = 1$) because no single indicator should be privileged. Fixing the factor innovation variance makes the units uniform across indicators and avoids sensitivity to the choice of anchor series.

Sign. The sign of f_t is anchored through the principal components initialization. The first principal component of the standardized indicator panel, used as the EM starting value, loads positively on income indicators. The EM solution inherits this orientation and produces a final factor with positive loadings on income and asset value indicators and negative loadings on credit stress indicators (full loading patterns in Section 6). Higher FFCI values therefore correspond to stronger agricultural financial conditions. This convention is the inverse of the NFCI (Brave and Butters, 2011), where positive values indicate tighter financial conditions. We adopt the positive-favorable convention because it aligns with the natural sign of the dominant variation pattern in the data and is more intuitive for an agricultural audience.

Loadings. Given these two normalizations, all 127 loadings are freely estimated by the EM algorithm without ex ante sign restrictions. This is essential because the sign of the relationship between many indicators and the latent factor is theoretically ambiguous, as discussed in Section 3. The free-loading approach lets the data's covariance structure determine these signs empirically.

[2]The Online Appendix provides full state-space details.

Estimation

We estimate the model using the EM algorithm with principal component analysis (PCA) initialization, following Stock and Watson (2002), and apply it in the state-space setting following Shumway and Stoffer (1982) and Doz et al. (2012). The AR(1) idiosyncratic specification is accommodated by augmenting the state vector to include the idiosyncratic processes as additional states, following Bańbura and Modugno (2014). The EM algorithm alternates between computing smoothed factor and idiosyncratic state estimates via the Kalman smoother (E-step) and updating parameters using closed-form expressions (M-step). This approach handles the high-dimensional state vector without evaluating numerical gradients. We estimate the model in MATLAB using the Mixed-Frequency State Space (MFSS) toolbox of Brave et al. (2022), with custom M-step routines for the EM parameter updates. Convergence diagnostics (number of iterations, log-likelihood trajectory, BIC) appear in the Online Appendix.

As a robustness check, we estimate a restricted specification in which the idiosyncratic component of net cash income (the first-indexed series in the panel) follows an AR(1) process, while the remaining 126 idiosyncratic errors are treated as white noise. BIC strongly prefers the full specification. Details and the model comparison are relegated to the Online Appendix.

Standardization and Interpretation

Following standard practice in the literature (Brave and Butters, 2011; Hakkio et al., 2009), we normalize the smoothed factor to zero mean and unit standard deviation over the estimation sample (trimmed to March 2025 to avoid end-of-sample artifacts). The resulting index is interpreted in standard deviation units: positive values indicate financial conditions stronger than the historical average, negative values indicate weaker conditions. For completeness, a reading of -2, for example, indicates conditions that are two standard deviations below the sample mean.

Decomposition

The estimated loadings enable decomposition of the index into contributions by indicator category. Let $c_{i,t}$ denote the contribution of indicator i at time t, defined as

$$c_{i,t} = \hat{\lambda}_i \, \tilde{y}_{i,t}, \tag{5}$$

where $\hat{\lambda}_i$ is the EM-estimated loading from Equation 2 and $\tilde{y}_{i,t}$ is the standardized indicator value. Aggregating within categories and applying proportional normalization so that sub-indices sum to the smoothed factor at each date yields a decomposition showing which dimensions of financial conditions drive the index during different episodes (Brave and Butters, 2012). This decomposition distinguishes, for example, whether deterioration originates in credit markets, commodity prices, or farm balance sheets, information directly relevant to the design of policy responses and to operational decisions by agricultural lenders and operators.

6 Results

The Farm Financial Conditions Index

Figure 1 presents the FFCI from January 1990 through March 2025 alongside its decomposition into the five economic categories defined in Section 4. The black line is the smoothed factor, standardized to zero mean and unit standard deviation over the trimmed estimation sample. Positive values indicate financial conditions stronger than the historical average; negative values indicate weaker conditions. The colored bars show each indicator category's contribution to the index at each date, computed as the sum of standardized indicator values weighted by their estimated loadings and proportionally normalized so the categories sum to the smoothed factor each month.

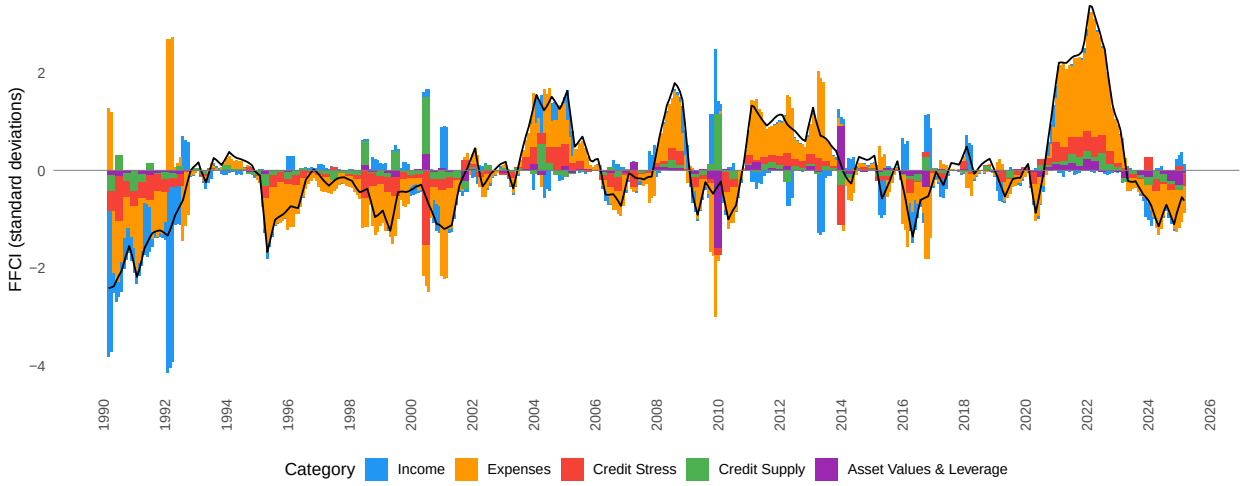


Figure 1: Farm Financial Conditions Index (FFCI) and decomposition into five economic categories, January 1990 through March 2025 (monthly). The FFCI (black line) is the common factor estimated from 127 mixed-frequency indicators, standardized to zero mean and unit standard deviation over the trimmed sample. Positive values indicate financial conditions stronger than the historical average. Colored bars show category contributions, computed as standardized indicator values weighted by estimated factor loadings and proportionally normalized so that the categories sum to the smoothed factor at each month.

The index identifies several periods of sustained departure from neutral conditions, corresponding to historically recognized eras of agricultural financial stress or expansion. The early 1990s show persistently negative conditions through the first half of the decade, the residual stress of the 1980s farm debt crisis as the sector worked through elevated delinquencies and tight credit conditions (Barnett, 2000; Key et al., 2019). A sustained positive regime emerges from 2003 through 2013, the multi-year "golden era" of US agriculture identified in the literature (Zhang and Tidgren, 2018; Key et al., 2019; Boehlje et al., 2011), with the index reaching local peaks as commodity prices, exports, and farmland values rose in successive surges. Notably, the index omits the 2008 financial crisis as a stress period. That year, the agricultural sector saw record commodity prices while the broader economy contracted, showing that agricultural financial conditions can decouple from macroeconomic cycles (Key et al., 2019). The 2014–2017 period shows a moderate but per-

sistent decline as commodity prices retreated and farm income fell sharply from its early-decade peak (Zhang and Tidgren, 2018). The most prominent feature is the 2020–2022 surge to a sample peak of +3.21 SD in early 2022, coinciding with record commodity prices, pandemic-era support programs, and historic farm income (Giri et al., 2024). The subsequent decline through 2023–2025 reflects normalizing conditions as commodity prices retreated and temporary support concluded, consistent with the "check engine light" assessments documented in recent practitioner reports (Ifft et al., 2026; Kohl, 2026; Langemeier and Colussi, 2026). The next subsection examines the two most pronounced eras: the early-1990s post-crisis stress and the 2020–2022 surge.

Neutral conditions (between ±1 SD) prevail in approximately 71 percent of the sample months. The five economic categories carry distinctive loading patterns that connect to the four-channel conceptual framework developed in Section 3. Income carries a mean loading of +3.28 across 12 indicators, with net cash farm income at $\hat{\lambda}_i = +6.56$. Expenses average +4.29 across 15 indicators, loading positively because rising input costs co-move with high agricultural activity and strong commodity prices. Asset Values & Leverage average +3.75 across 22 indicators, capturing the collateral channel. Credit Stress, the only category with a negative mean loading, averages −4.13 across 41 delinquency and interest rate indicators, reflecting that elevated delinquencies and tight loan terms pull the index down. Credit Supply averages +1.02 across 37 loan volume and availability indicators, with contracting loan volumes pulling the index down. Income contributions appear as sharp intermittent jumps in the decomposition figure because the underlying USDA series are released only annually. The state-space framework distributes the annual signal across the months in which it is observed. Asset Values & Leverage contributes modestly throughout the sample, reflecting the slow-moving nature of farmland prices and balance sheet adjustments. The median R^2 across all 127 indicators is about 4 percent, consistent with large-N factor models where the common component captures pervasive co-movement while most individual-series variation is idiosyncratic (Brave and Butters, 2012).

Two Defining Episodes

Figures 2 and 3 examine the two episodes that bookend the FFCI's range, illustrating how the channels combine during periods of acute stress and strong conditions.

The 1990–1995 panel captures the recovery from the 1980s farm debt crisis. The FFCI begins the figure window at −2.07 SD in February 1990 and remains below −1 SD for twenty consecutive months as the sector worked through residual financial stress. The dominant negative contribution comes from Credit Stress, with bank capital ratios, loan-term stress measures, and ag-bank delinquency indicators running between 1.5 and 2 standard deviations above their long-run means throughout the early 1990s. Expense indicators are also depressed during this period (input prices for fertilizer and other agricultural inputs were well below mean), reflecting the disinflationary environment and muted agricultural activity of the post-crisis recovery. Income indicators contribute only mildly to the decline. This channel mix maps to the credit and cost channels of the conceptual framework (Section 3). The credit channel is the dominant driver, reflecting the insti-

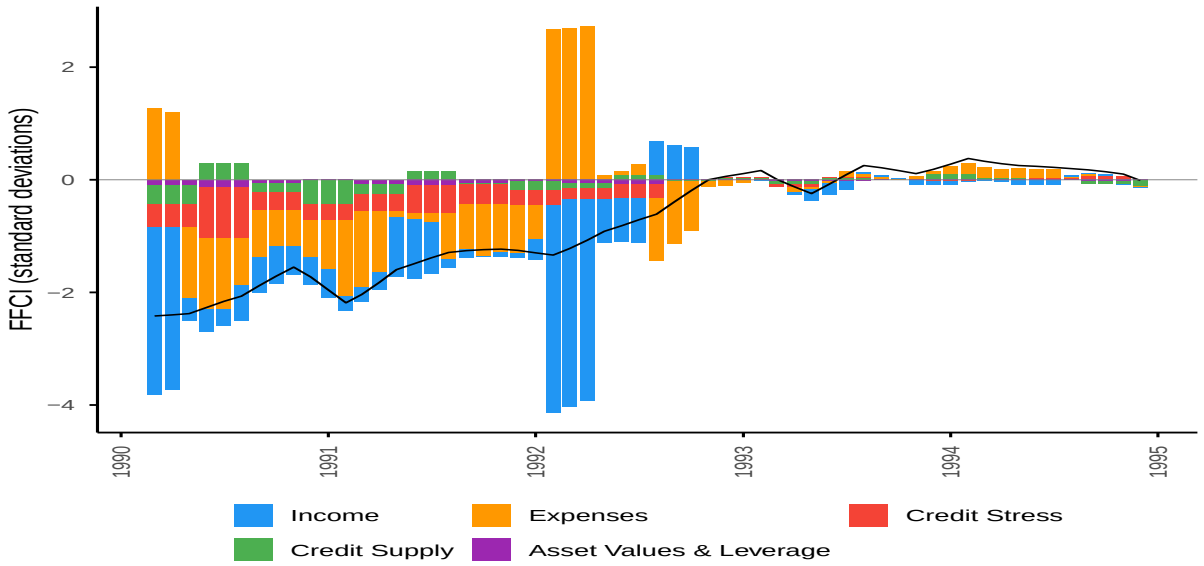


Figure 2: Post-farm-crisis stress episode, 1990–1995 (monthly). The FFCI (black line) is the Farm Financial Conditions Index, standardized to zero mean and unit standard deviation over the sample, with positive values indicating stronger-than-average conditions. The index declines through 1991 and recovers to neutral conditions by 1993. Colored bars show category contributions to the index, with categories defined as in Figure 1.

tutional residue of the 1980s crisis (impaired bank balance sheets and elevated borrower distress as predicted by Calomiris et al. (1986)), while the cost channel reflects the broader disinflationary environment. Income channel weakness, the most visible feature of the original 1980s crisis itself, has largely abated by this point in the recovery, consistent with the USDA-ERS sectoral series documented in Key et al. (2019). The index recovers gradually, crossing zero in mid-1993 and stabilizing near neutral conditions through 1994–1995 as commodity prices firmed and delinquency rates returned to historical averages (Barnett, 2000). A single visually prominent contribution in early 1992 reflects the annual release of USDA income data, which arrives once a year and produces a large month-of-arrival contribution. This is a known feature of mixed-frequency factor models with infrequent series and does not indicate a turning point in conditions.

The 2020–2023 panel captures the commodity boom and subsequent reversal. The FFCI begins with a brief negative period in early 2020 (COVID-related disruption), rises rapidly through 2021, and reaches the sample peak of +3.21 SD in January 2022. The index remains above +1 SD for twenty-seven consecutive months, the longest sustained departure in the sample. This is the only episode in which all four channels of the conceptual framework (Section 3) contribute favorably in concert. The dominant positive contributions come from Expenses (input prices for fertilizer and building materials running roughly 1.1 SD above their long-run means as the commodity surge passed through to input markets) and Credit Stress (delinquency and loan-terms stress indicators running well below mean as record income kept borrowers current). Credit Supply expanded (loan volumes above mean), Asset Values strengthened (farmland values and bank balance sheet ratios favorable), and Income indicators were uniformly positive though their contribution to the index was smaller in magnitude. The breadth of channel co-movement during this period reflects

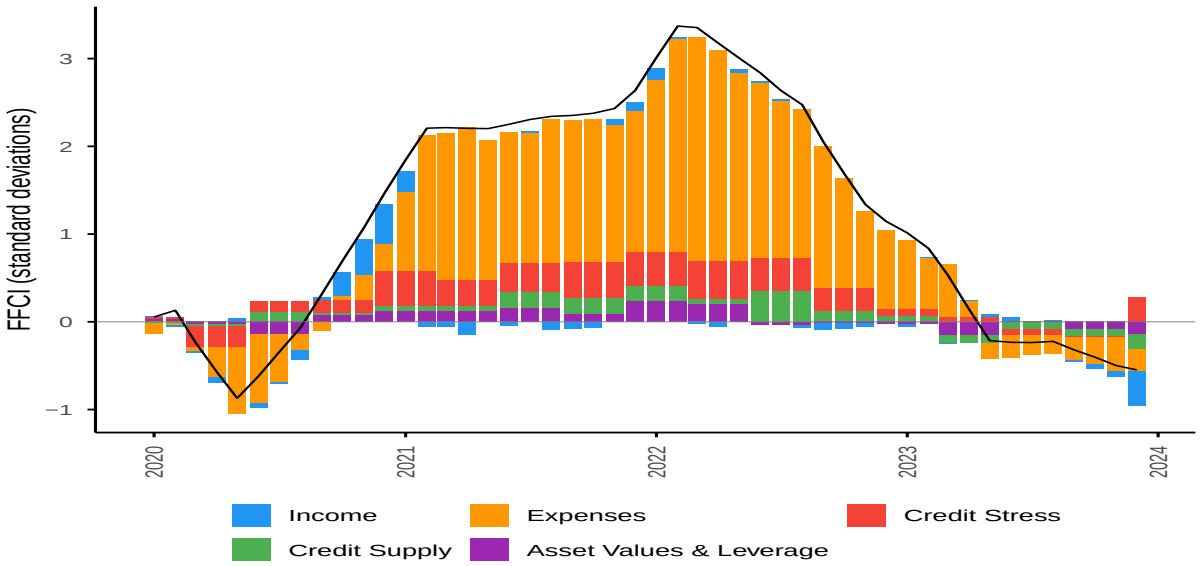


Figure 3: Commodity boom and reversal, 2020–2023 (monthly). The FFCI (black line) is the Farm Financial Conditions Index, standardized to zero mean and unit standard deviation over the sample, with positive values indicating stronger-than-average conditions. The index reaches the sample peak of +3.2 SD in early 2022 before declining as commodity prices retreated and temporary policy support concluded. Colored bars show category contributions to the index, with categories defined as in Figure 1. Expenses (orange) drive the bulk of the positive contribution during the boom.

the unusual combination of record commodity prices, pandemic-era support programs including the Coronavirus Food Assistance Program, and historic farm income (Giri et al., 2024). The index declines through 2022–2023 as commodity prices retreat, government support ends, and input costs continue to compress margins; it crosses zero in mid-2023 and trends into negative territory by year-end. Recent assessments trace this reversal in detail and document its operational consequences for the sector (Langemeier and Colussi, 2026; Kohl, 2026).

Together, these episodes illustrate two different dynamics. The post-farm-crisis trough demonstrates how multiple channels can co-deteriorate during sectoral stress, while the 2020–2022 boom illustrates how a single dominant channel (Expenses) can drive the index to its sample extreme.

Subindex Construction

The decomposition shown in Figures 1 – 3 relies on a set of *subindexes*, one for each indicator category. We define the subindex for category c at time t as the proportionally normalized sum of contributions from indicators in that category:

$$\text{subindex}_{c,t} = \kappa_t \sum_{i \in c} \hat{\lambda}_i \, \tilde{y}_{i,t}, \quad \text{where } \kappa_t \text{ rescales so that } \sum_c \text{subindex}_{c,t} = \hat{f}_t. \tag{6}$$

A subindex represents the share of the FFCI's movement at time t attributable to one indicator category. Subindexes are not separate latent variables. They project the same common factor through different subsets of estimated loadings.

When we evaluate subindexes as predictors of farm financial distress in the validation analysis below, we test each in a separate univariate regression against Chapter 12 filings. The univariate setup is necessary because the subindexes are not independent. A joint regression would be collinear by construction. The univariate tests instead evaluate, for each category, whether its contribution to the FFCI carries predictive information about subsequent filings beyond what filings' own history provides.

Validation Against Chapter 12 Bankruptcy Filings

We validate the FFCI as a leading indicator of farm financial distress using Chapter 12 bankruptcy filings from the Federal Judicial Center's Integrated Database (https://www.fjc.gov/research/idb). Chapter 12, created by the Family Farmer Bankruptcy Act of 1986, provides a reorganization framework exclusively for family farmers. A filing represents a revealed-preference measure of extreme distress, since a farmer files only when conditions are severe enough that legal reorganization is preferable to continuing under current obligations.

We extract 7,956 individual filings from October 2007 through December 2024 and aggregate to monthly national counts. The Integrated Database provides monthly observations beginning in October 2007; earlier years are available only at annual frequency, which would mismatch the monthly resolution of the FFCI. The sample also falls entirely after the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005, which altered eligibility criteria and created a structural break in filing incentives (Dinterman et al., 2018).

Figure 4 plots the FFCI alongside monthly filings. The inverse relationship is visually apparent. Filings rise when the FFCI declines and fall when conditions improve.

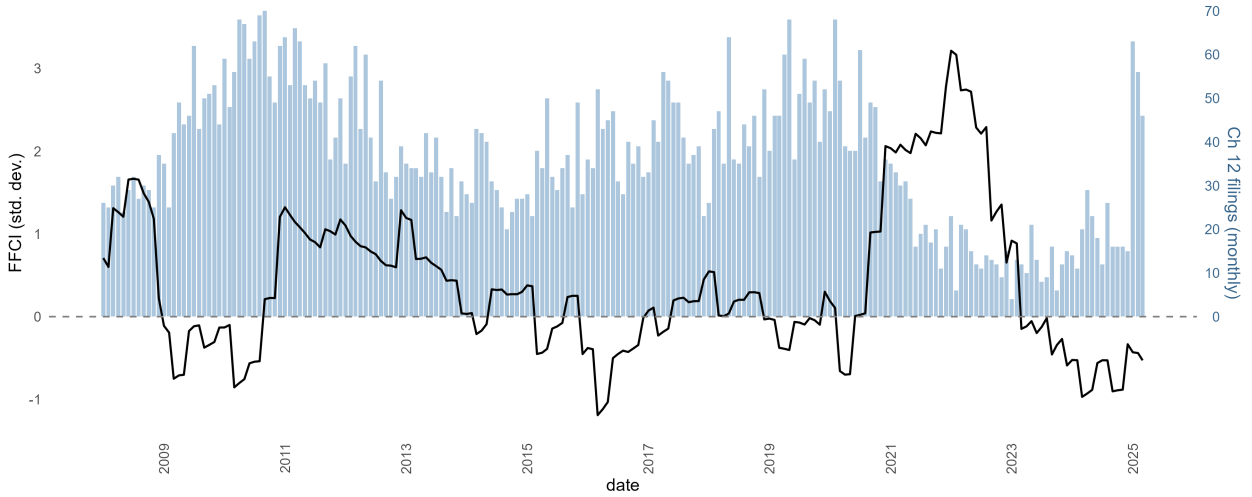


Figure 4: Farm Financial Conditions Index and monthly Chapter 12 bankruptcy filings, January 2008 through December 2024. The FFCI (black line, left axis) is standardized to zero mean and unit standard deviation. Chapter 12 filings (blue bars, right axis) are monthly counts of farm reorganization bankruptcies from the Federal Judicial Center Integrated Database. Filings rise when the FFCI declines. The lag between FFCI movements and filing responses is consistent with the 12-month lead identified in the cross-correlation analysis reported in Table 2.

Two limitations of this validation deserve note. First, Chapter 12 captures only farms with at least 50 percent of gross income from farming; smaller operators and farms with substantial off-farm income face distress through other channels, and the FFCI's relationship to severe distress among those operators is not measured here. Second, bankruptcy is a proxy for severe distress rather than a complete measure of agricultural financial conditions; the validation shows that the FFCI has predictive content for this outcome, not that it captures every dimension of conditions in the sector.

Lead/Lag Properties

Cross-correlation analysis reveals that the FFCI leads Chapter 12 filings by 12 months, with a moderate correlation of $r = -0.51$. A deterioration in the index today is associated with higher filings approximately one year later.

While the cross-correlations establish timing relationships, they do not test whether the FFCI contains predictive information beyond what is already embedded in the history of filings themselves. We assess this using Granger causality tests (Granger, 1969). For each index series x_t (the FFCI or a subindex), we estimate a bivariate predictive regression in which monthly Chapter 12 filings y_t are regressed on p lags of both filings and the index:

$$y_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j y_{t-j} + \sum_{j=1}^{p} \beta_j x_{t-j} + \varepsilon_t \tag{7}$$

The null hypothesis $H_0 : \beta_1 = \cdots = \beta_p = 0$ tests whether the index lags have any additional predictive power for filings beyond what filings' own history provides. We use $p = 12$ lags (one year of monthly history), chosen to span the lead times identified in the cross-correlation analysis rather than by an information criterion. We report robustness to alternative lag orders in the Online Appendix. We test the restriction with an F-test. To assess directionality, we also test the reverse specification (whether filings predict the index) by swapping x and y. A significant forward test with an insignificant reverse test supports unidirectional predictive precedence from financial conditions to filings.

Table 2 reports the lead times, cross-correlations, and Granger causality results for the aggregate index and five economic-category subindexes.

The FFCI and most subindexes significantly Granger-cause Chapter 12 filings. Credit Supply ($p = 0.002$) and Credit Stress ($p = 0.007$) carry the strongest predictive signal, consistent with the theoretical importance of credit channels in agricultural financial distress (Calomiris et al., 1986; Kuethe and Hubbs, 2020). Credit Supply is the only subindex for which the reverse test is also significant ($p = 0.008$), indicating a bidirectional predictive relationship. This is economically plausible. Rising bankruptcies impair agricultural bank balance sheets through loan losses and increased provisioning, which constrains subsequent lending capacity. The bidirectional finding for Credit Supply does not undermine its value as an early warning indicator (it signals first, with a 3-month lead) but does suggest that credit supply conditions both anticipate and respond to farm

Table 2: Lead/lag properties.

Series	Lead (months)	Peak r	Granger p	Reverse p
Credit Supply	3	−0.37	0.002	0.008
Expenses	6	−0.50	0.037	0.123
Credit Stress	12	−0.51	0.007	0.392
FFCI	**12**	**−0.51**	**0.013**	**0.669**
Income	13	−0.33	0.255	0.210
Asset Values & Leverage	24	−0.48	0.013	0.333

Notes: The table reports lead times and Granger causality results for the FFCI aggregate index and the five economic-category subindexes against monthly Chapter 12 farm bankruptcy filings, January 2008 through December 2024. Lead times (months) and peak cross-correlations r are estimated from the cross-correlation function. Granger p-values test whether 12 lags of the index improve prediction of filings beyond filings' own 12-lag history. Reverse p tests whether filings Granger-cause the index. The bolded row reports results for the aggregate FFCI. Subindex construction is defined in Equation (6). Robustness to alternative lag orders and HAC inference is reported in the Online Appendix.

financial distress, consistent with the financial accelerator mechanism described by Kiyotaki and Moore (1997).

Predictive precedence runs from conditions to filings, not the reverse. The reverse Granger test for the aggregate FFCI is insignificant ($p = 0.669$), supporting unidirectional predictive precedence from financial conditions to bankruptcy outcomes. This result is robust to heteroskedasticity and autocorrelation-consistent (HAC) inference, with HAC-robust $p < 0.001$ for the forward test and $p = 0.118$ for the reverse test (Online Appendix). We emphasize that Granger causality establishes predictive precedence (whether past values of the FFCI improve forecasts of filings beyond filings' own history), not a mechanistic claim that movements in the FFCI *cause* bankruptcy filings. Establishing a structural causal relationship would require identifying exogenous variation in financial conditions and ruling out reverse causation through alternative channels, which is beyond the scope of this validation exercise. The Online Appendix discusses the scope and limitations of this interpretation.

The subindex lead times reveal a sequential pattern. Credit Supply signals first at three months, as banks reduce lending volumes. Expenses follow at six months, capturing cost pressures. Credit Stress manifests at twelve months as delinquencies rise. Asset Values respond last at twenty-four months, reflecting slow farmland price adjustments. This ordering matches the credit channel transmission described by Calomiris et al. (1986) and is consistent across lag orders $p \in \{3, 6, 12, 18, 24\}$ (Online Appendix). The aggregate FFCI's 12-month lead corresponds to the weighted average of these channel-specific lead times, with the Credit Stress component (which carries the largest absolute loadings) anchoring the aggregate response.

The findings hold when the F-test is replaced with a Newey and West (1987) HAC Wald test, and across alternative lag orders $p \in \{3, 6, 12, 18, 24\}$ (Online Appendix). The finding that Income does not achieve Granger significance ($p = 0.255$) is consistent with the lower frequency of income data (annual USDA ERS measures), which reduces power in a monthly regression framework.

7 Discussion

The conceptual framework in Section 3 generated four predictions for the empirical analysis. This section evaluates each prediction against the results reported in Section 6 and positions the findings within the corpus of related research.

Predicted and Observed Sign Patterns

The first prediction concerned the signs with which indicators load on the common factor. Income, asset values, and credit supply indicators were predicted to load positively; credit stress indicators negatively; expenses ambiguously. The estimated loadings confirm each predicted pattern. Loading magnitudes by category are reported in Section 6. Income, asset value, and credit supply indicators load positively on average, credit stress indicators load negatively, and expenses load positively, revealing that the empirical sign of the cost channel is procyclical, with input prices rising during periods of high agricultural activity rather than signaling stress in isolation.

These patterns are consistent with the four-channel framework of Calomiris et al. (1986) and the financial accelerator mechanism of Kiyotaki and Moore (1997). They also distinguish this application from Shonkwiler and Moss (1993), whose four annual indicators (inflation, unemployment, debt-to-equity, and rate of return on farm assets) were each pre-selected to capture a specific dimension of stress with a theoretically predictable sign. With 127 indicators spanning the full set of agricultural financial channels, including 78 credit measures with ambiguous theoretical signs, the FFCI requires no such pre-selection. The data's covariance structure determines the signs through the free-loading specification.

The second prediction was that a single dominant factor would suffice. The eigenvalue ratio test of Ahn and Horenstein (2013) selects $r = 1$ with a first-to-second eigenvalue ratio of 10.8, and the first principal component explains 53 percent of total cross-sectional variance. These statistics, reported in Section 5, support the single-factor specification adopted throughout.

The result aligns with the broader factor-based financial conditions literature. Brave and Butters (2011) construct the NFCI as a single common factor from over 100 indicators; Hakkio et al. (2009) similarly extract a single Kansas City Financial Stress Index. The agricultural sector exhibits the same integrated dynamics. The integration is consistent with the feedback mechanisms identified in Section 3 and documented for agriculture by Kuethe and Hubbs (2020) and Calomiris et al. (1986).

Sequential Transmission Through Channels

The third prediction was that the channels would not move synchronously, with credit supply adjusting before observable stress and asset values responding last. The subindex lead times reported in Table 2 confirm this ordering.

This staged pattern is consistent with the credit channel transmission of Calomiris et al. (1986) and the financial accelerator dynamics of Kiyotaki and Moore (1997) and Bernanke et al. (1999).

It also aligns with Kuethe and Hubbs (2020), who document that the agricultural credit cycle leads farm loan delinquencies and bankruptcies by multiple years. Briggeman et al. (2009) provide a closely related precedent at the lender-side level, showing via Granger causality that agricultural land values lead net loan charge-offs by multiple years and that this leading relationship operates at both commercial agricultural banks and the Farm Credit System. The contribution here is the explicit decomposition of the staged transmission. Earlier work documents that credit conditions lead distress; it does not separate credit supply from credit stress as distinct dimensions of the same broader cycle. The empirical separation provides a graduated framework for early warning that no single aggregate indicator can support.

Leading Content for Severe Distress

The fourth prediction was that the index would carry leading information for severe financial distress. The Chapter 12 validation reported in Section 6 confirms a twelve-month lead at the aggregate level, with Granger causality running from conditions to filings ($p = 0.013$) but not the reverse ($p = 0.669$).

This finding complements existing work on agricultural bankruptcy determinants. Dinterman et al. (2018) analyze quarterly Chapter 12 filings after the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005, identifying farm sector debt and interest rates as significant predictors, but using indicators rather than a composite measure of financial conditions. The FFCI provides the composite framework those individual predictors imply and shows that aggregate financial conditions carry information beyond what individual indicators contribute in isolation. The unidirectional Granger result also addresses a potential concern. Bankruptcy filings might mechanically affect subsequent credit measures, but the data do not support a reverse predictive relationship from filings to the aggregate index.

The FFCI extends the factor-based financial conditions framework established by Brave and Butters (2011) for the U.S. macroeconomy and Hakkio et al. (2009) for the broader financial system. It serves the same diagnostic function for agriculture that the National Financial Conditions Index and Kansas City Financial Stress Index serve for general monetary policy and financial stability monitoring, including their established role as leading indicators of severe macroeconomic distress (Adrian et al., 2019).

The closest predecessor for agricultural measurement is Shonkwiler and Moss (1993), which used four annual indicators in a static confirmatory factor analysis. The FFCI extends this in three respects: scale (127 versus 4 indicators), temporal resolution (monthly versus annual), and indicator breadth (including credit measures with theoretically ambiguous signs identified empirically via free loadings). The agricultural finance literature has also produced a generation of indicator dashboards and practitioner assessments (Ifft et al., 2026; Rural and Farm Finance Policy Analysis Center, 2026; Kohl, 2026; Langemeier and Colussi, 2026). These provide timely, expert-interpreted monitoring of individual measures. The FFCI complements them by aggregating the conflicting signals they identify into a formal, continuously updated framework with a historical benchmark

for comparison.

8 Conclusion

This paper develops the first comprehensive, mixed-frequency agricultural financial conditions index. The Farm Financial Conditions Index synthesizes 127 indicators observed at monthly, quarterly, and annual frequencies into a single continuously updated measure of agricultural financial health from 1989 to the present. The empirical patterns documented in Section 6 and discussed in Section 7 show that the index recovers the predicted theoretical signs across channels, identifies a sequential transmission pattern through the credit channels, and carries leading information on severe distress measured by Chapter 12 bankruptcy filings.

Policy and Managerial Implications

The FFCI addresses a specific institutional gap. Despite recurring crises that have triggered tens of billions of dollars in emergency government interventions, the agricultural sector has lacked a formal, continuously updated measure of financial conditions that synthesizes conflicting indicator signals. The index resolves this problem in three ways.

First, the decomposition identifies the *source* of emerging stress, which matters for policy design and operational risk management. The 2014–2017 decline originated in commodity price deterioration (Expenses) before propagating to credit markets, suggesting that income support programs were the appropriate first response. The 1990–1992 post-crisis trough, by contrast, involved sustained negative contributions across Income, Expenses, and Credit Stress simultaneously, warranting broad-based intervention.

Second, the sequential lead times across subindexes provide a *staging* framework for early warning. Credit Supply indicators (loan volumes, fund availability, and lending terms) signal first, offering the earliest actionable information. Credit Stress indicators (delinquencies and charge-offs) confirm the diagnosis with a longer lag. Monitoring these subindexes in sequence, rather than waiting for a single threshold breach, enables graduated policy responses and lender risk-management decisions.

Third, the index provides a continuous historical baseline against which current conditions can be assessed. The post-2022 deterioration in the FFCI, which through the end of the analytical sample (March 2025) had been sustained for over twelve months, can be compared directly to past stress episodes in both magnitude and duration. This historical anchoring is absent from ad hoc indicator dashboards that lack a formal aggregation framework. Such comparisons assume that the relationships between indicators and the latent factor remain stable over time, an assumption discussed further below.

These three roles translate into concrete actionable signals. As of the end of the analytical sample, the FFCI's sustained negative reading and the relative contributions of Credit Stress and Expenses together suggest that the current downturn is unfolding through the cost and credit chan-

nels rather than as a broad systemic episode, with implications for the type of policy intervention most likely to be effective. The same channel-level information is directly relevant to agricultural lenders, who must allocate underwriting attention across credit supply and stress channels, and to operators, who must position working capital and debt-service strategies against the staged transmission pattern documented above. Real-time updates to the index as new mixed-frequency data arrive provide a continuously available diagnostic for both policy and management.

Limitations and Future Directions

Several limitations warrant consideration. The index reflects aggregate national conditions and does not capture substantial heterogeneity across commodities, regions, or farm sizes (Ifft et al., 2026; Kohl, 2026). The model assumes stable relationships between indicators and the common factor over the sample period. However, structural changes, such as the increased role of non-traditional lenders (Kohl, 2026), may undermine this assumption. Future research should investigate potential structural instability in factor loadings using rolling or recursive estimation and formal break tests. If instability is identified, models with time-varying parameters or regime-switching could more accurately represent evolving financial conditions in agriculture.

The comparison with Chapter 12 filings indicates predictive precedence rather than structural causation. The Granger causality approach does not fully address contemporaneous endogeneity, although timing-related factors may partially mitigate this issue. Broader validation and backtesting, including comparisons with USDA farm income, liquidity, solvency, and Federal Reserve Bank credit condition data, could further support the economic relevance of the FFCI. Additionally, incorporating measures of loan delinquencies and nonperforming loans from regulatory data could help assess whether declines in the FFCI precede episodes of credit distress.

Survey-based indicators provide an independent means of validation. For instance, the Purdue University/CME Group Ag Economy Barometer offers data on producers' current and expected financial conditions. Comparing the FFCI with these indices, along with survey-based measures of investment intentions and farmland value expectations, could reveal whether the FFCI aligns with producer sentiment. Although the Ag Economy Barometer covers only the post-2015 period, it remains a valuable resource for complementary validation during recent episodes of financial stress and recovery.

Further validation should assess whether the FFCI identifies farm-sector stress not apparent in broader macro-financial indicators. Comparisons with the Chicago and St. Louis Federal Reserve indices, credit and term spreads, and lending standards could demonstrate the FFCI's incremental value. Beyond cross-sectional analysis, one could conduct recursive and pseudo-out-of-sample backtesting to evaluate the FFCI's ability to anticipate episodes of financial deterioration. Assess whether changes in the FFCI precede shifts in farm income, loan performance, producer sentiment, or bankruptcy filings, and whether restrictive readings align with recognized stress periods. Out-of-sample forecast accuracy and warning signal analysis would help clarify whether the FFCI functions primarily as a contemporaneous summary or as an early-warning indicator of financial

stress in the farm sector.

Several natural extensions of the framework are supported. The most immediate extension involves constructing commodity-specific sub-indices to distinguish the dynamics of crop and livestock sectors, which can diverge significantly during periods of price asymmetry across commodity groups. The mixed-frequency framework used in this study can be applied directly to sector-specific indicator panels. Another priority is integrating the FFCI into a formal nowcasting framework, such as generating real-time forecasts of annual farm income before the release of official USDA estimates. The 12-month lead identified in the validation analysis indicates that the index contains forecast-relevant information, and explicit forecasting models could translate this lead into actionable predictions. Additional extensions, such as developing state- or production-region-level indices to capture geographic heterogeneity and implementing time-varying parameter specifications to address structural changes in agricultural financial markets, remain valuable but are constrained by data availability and methodological challenges.

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A Data Appendix

Table A.1: Agricultural Financial Indicators Grouped by Economic Category and Sorted by Absolute Inter-group Weights

Financial Indicator[1]	Source[2]	Start Date	Freq.	Trans.[3]	Weight[4]
Income (12 indicators)					
Farm Income - Kansas City	Dist. Surv.	Jun 2002	Q	LV	1.14
Farm Income - St. Louis	Dist. Surv.	Jun 2012	Q	DLV	1.06
Farm Income - Minneapolis	Dist. Surv.	Mar 2001	Q	DLN	1.00
Net Cash Income	ERS	Dec 1910	A	DLN	0.94
Crop Cash Receipts	ERS	Dec 1910	A	DLN	0.90
Livestock and Products Cash Receipts	ERS	Dec 1910	A	DLN	0.82
Prices Received Index - CROP TOTALS	NASS	Jan 1910	M	DLN	-0.26
Prices Received Index - ANIMAL TOTALS	NASS	Aug 1909	M	DLN	0.16
Prices Received Index - COMMODITY TOTALS	NASS	Aug 1909	M	DLN	-0.12
Direct Government Payments	ERS	Dec 1933	A	DLN	-0.12
Gross Value Added: GDP: Business: Farm	FRED	Mar 1960	Q	DLN	0.07
Exports of Agricultural Goods	FRED	Mar 1967	Q	DLN	0.05
Expenses (15 indicators)					
District Survey 008 - Kansas City	Dist. Surv.	Jun 2002	Q	LV	1.13
Prices Paid Index - FERTILIZER TOTALS	NASS	Mar 1923	M	LV	1.08
District Survey 008 - St. Louis	Dist. Surv.	Jun 2012	Q	DLN	1.03
Prices Paid Index - INTEREST	NASS	Jan 1910	M	LV	0.99
District Survey 008 - Minneapolis	Dist. Surv.	Mar 2001	Q	DLV	0.97
Prices Paid Index - BUILDING MATERIALS	NASS	Mar 1923	M	DLN	0.91
Total Production Expenses (Including Operator Dwellings)	ERS	Dec 1910	A	DLN	0.81
Prices Paid Index - AG SERVICES RENT	NASS	Jan 1985	M	DLN	0.64
Prices Paid Index - LABOR	NASS	Mar 1923	M	DLN	0.61
Prices Paid Index - MACHINERY TOTALS	NASS	Jan 1995	M	DLN	0.55
Prices Paid Index - ANIMAL TOTALS	NASS	Mar 1923	M	DLN	0.50
Employment Level - Agriculture and Related Industries, Self-Employed Workers, Unincorporated	FRED	Jan 1960	M	DLN	-0.26
Prices Paid Index - FUELS	NASS	Jan 1950	M	DLN	0.21
Employment Level - Agriculture and Related Industries, Wage and Salary Workers	FRED	Jan 1960	M	DLN	0.10
Prices Paid Index - FEED	NASS	Mar 1923	M	DLN	-0.05
Credit Stress (41 indicators)					
Call Report Series A008	Call Rpt.	Mar 1987	Q	LV	-1.13

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Table A.1 continued

Financial Indicator[1]	Source[2]	Start Date	Freq.	Trans.[3]	Weight[4]
Call Report Series B007	Call Rpt.	Mar 2001	Q	DLV	-1.13
Call Report Series B011	Call Rpt.	Mar 2001	Q	DLV	-1.13
Call Report Series B010	Call Rpt.	Mar 2001	Q	DLV	-1.13
Call Report Series B006	Call Rpt.	Mar 2001	Q	DLV	-1.12
Call Report Series B005	Call Rpt.	Mar 2001	Q	DLV	-1.11
Call Report Series B008	Call Rpt.	Mar 2001	Q	DLV	-1.11
Average Effective Interest Rate - Farm Machinery and Equipment	Terms Surv.	Mar 1977	Q	LV	-1.11
Call Report Series A011	Call Rpt.	Mar 1987	Q	LV	-1.11
Call Report Series B004	Call Rpt.	Mar 2001	Q	DLV	-1.10
District Survey 003 - Kansas City	Dist. Surv.	Mar 1991	Q	LV	1.10
District Survey 004 - St. Louis	Dist. Surv.	Jun 2012	Q	DLV	-1.10
Average Effective Interest Rate - Other Current Operating Expenses	Terms Surv.	Mar 1977	Q	LV	-1.10
Average Effective Interest Rate - Feeder Livestock	Terms Surv.	Mar 1977	Q	LV	-1.10
Average Effective Interest Rate - All Loans	Terms Surv.	Mar 1977	Q	LV	-1.10
Call Report Series B009	Call Rpt.	Mar 2001	Q	DLV	-1.10
District Survey 005 - Dallas	Dist. Surv.	Mar 1991	Q	LV	-1.09
Average Effective Interest Rate - Other Livestock	Terms Surv.	Mar 1977	Q	LV	-1.09
District Survey 005 - St. Louis	Dist. Surv.	Jun 2012	Q	DLN	-1.08
District Survey 003 - Dallas	Dist. Surv.	Mar 1991	Q	LV	1.08
District Survey 003 - Chicago	Dist. Surv.	Mar 1991	Q	LV	1.08
Call Report Series A004	Call Rpt.	Mar 1991	Q	DLV	-1.06
District Survey 004 - Dallas	Dist. Surv.	Mar 1991	Q	LV	-1.06
District Survey 004 - Chicago	Dist. Surv.	Mar 1991	Q	LV	-1.06
District Survey 005 - Chicago	Dist. Surv.	Mar 1991	Q	LV	-1.06
Call Report Series A005	Call Rpt.	Mar 1991	Q	DLN	-1.03
District Survey 003 - St. Louis	Dist. Surv.	Jun 2012	Q	DLV	1.01
Call Report Series A007	Call Rpt.	Mar 1991	Q	LV	-1.01
Call Report Series A010	Call Rpt.	Mar 1987	Q	LV	-0.97
District Survey 005 - Kansas City	Dist. Surv.	Mar 1991	Q	LV	-0.95
District Survey 004 - Minneapolis	Dist. Surv.	Mar 2001	Q	DLN	-0.95
District Survey 003 - Minneapolis	Dist. Surv.	Mar 2001	Q	DLN	0.95
District Survey 004 - Kansas City	Dist. Surv.	Mar 1991	Q	DLN	-0.92
Call Report Series A009	Call Rpt.	Mar 1987	Q	DLN	-0.90
Share of Loans with Floating Rate - Other Current Operating Expenses	Terms Surv.	Mar 1977	Q	DLN	0.74
Share of Loans with Floating Rate - All Loans	Terms Surv.	Mar 1977	Q	DLN	0.64
Call Report Series A006	Call Rpt.	Mar 1991	Q	LV	0.54
Share of Loans with Floating Rate - Other Livestock	Terms Surv.	Mar 1977	Q	DLN	-0.46

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Table A.1 continued

Financial Indicator[1]	Source[2]	Start Date	Freq.	Trans.[3]	Weight[4]
Share of Loans with Floating Rate - Farm Machinery and Equipment	Terms Surv.	Mar 1977	Q	DLN	0.44
District Survey 005 - Minneapolis	Dist. Surv.	Mar 1994	Q	DLN	-0.37
Share of Loans with Floating Rate - Feeder Livestock	Terms Surv.	Mar 1977	Q	DLN	-0.02
Credit Supply (37 indicators)					
Number of Non-Real Estate Bank Loans - Other Livestock	Terms Surv.	Mar 1977	Q	LV	-1.08
Average Maturity of Non-Real Estate Bank Loans - All Loans	Terms Surv.	Mar 1977	Q	LV	1.06
District Survey 002 - St. Louis	Dist. Surv.	Jun 2012	Q	DLV	-1.03
District Survey 002 - Minneapolis	Dist. Surv.	Mar 1994	Q	LV	1.00
Number of Non-Real Estate Bank Loans - Other Current Operating Expenses	Terms Surv.	Mar 1977	Q	LV	-1.00
Call Report Series A003	Call Rpt.	Jun 1964	Q	DLN	0.96
Total Agricultural Loans at All Commercial Banks	Call Rpt.	Jun 1964	Q	DLN	0.95
Call Report Series B001	Call Rpt.	Jun 1964	Q	DLN	0.95
Call Report Series B003	Call Rpt.	Jun 1964	Q	DLN	0.94
Average Maturity of Non-Real Estate Bank Loans - Feeder Livestock	Terms Surv.	Mar 1977	Q	LV	0.93
Demand for Loans - St. Louis	Dist. Surv.	Jun 2012	Q	DLN	-0.93
District Survey 002 - Chicago	Dist. Surv.	Mar 1991	Q	LV	0.91
Average Maturity of Non-Real Estate Bank Loans - Farm Machinery and Equipment	Terms Surv.	Mar 1977	Q	LV	0.90
Total Number of Agricultural Banks	Call Rpt.	Jun 1964	Q	DLN	0.89
District Survey 002 - Kansas City	Dist. Surv.	Mar 1991	Q	LV	0.87
Average Size of Non-Real Estate Bank Loans - Other Current Operating Expenses	Terms Surv.	Mar 1977	Q	DLN	-0.87
Call Report Series B002	Call Rpt.	Jun 1964	Q	DLN	0.85
Volume of Non-Real Estate Bank Loans - Other Current Operating Expenses	Terms Surv.	Mar 1977	Q	LV	0.83
Average Maturity of Non-Real Estate Bank Loans - Other Current Operating Expenses	Terms Surv.	Mar 1977	Q	LV	0.81
Average Size of Non-Real Estate Bank Loans - All Loans	Terms Surv.	Mar 1977	Q	DLN	-0.79
Number of Non-Real Estate Bank Loans - Farm Machinery and Equipment	Terms Surv.	Mar 1977	Q	DLN	-0.75
Volume of Non-Real Estate Bank Loans - All Loans	Terms Surv.	Mar 1977	Q	DLN	-0.74

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Table A.1 continued

Financial Indicator[1]	Source[2]	Start Date	Freq.	Trans.[3]	Weight[4]
Volume of Non-Real Estate Bank Loans - Farm Machinery and Equipment	Terms Surv.	Mar 1977	Q	DLN	-0.73
Average Maturity of Non-Real Estate Bank Loans - Other Livestock	Terms Surv.	Mar 1977	Q	LV	0.69
Demand for Loans - Chicago	Dist. Surv.	Mar 1991	Q	DLN	-0.68
Average Size of Non-Real Estate Bank Loans - Farm Machinery and Equipment	Terms Surv.	Mar 1977	Q	DLN	-0.46
Demand for Loans - Kansas City	Dist. Surv.	Mar 1991	Q	DLN	0.39
Volume of Non-Real Estate Bank Loans - Other Livestock	Terms Surv.	Mar 1977	Q	LV	-0.35
Call Report Series A002	Call Rpt.	Jun 1964	Q	DLN	0.33
Demand for Loans - Dallas	Dist. Surv.	Mar 1991	Q	DLN	-0.31
Average Size of Non-Real Estate Bank Loans - Other Livestock	Terms Surv.	Mar 1977	Q	DLN	-0.26
Demand for Loans - Minneapolis	Dist. Surv.	Mar 2002	Q	DLN	0.24
Volume of Non-Real Estate Bank Loans - Feeder Livestock	Terms Surv.	Mar 1977	Q	DLN	0.22
Number of Non-Real Estate Bank Loans - Feeder Livestock	Terms Surv.	Mar 1977	Q	DLN	0.21
Number of Non-Real Estate Bank Loans - All Loans	Terms Surv.	Mar 1977	Q	DLN	0.18
District Survey 002 - Dallas	Dist. Surv.	Mar 1991	Q	DLN	0.14
Average Size of Non-Real Estate Bank Loans - Feeder Livestock	Terms Surv.	Mar 1977	Q	DLN	0.09
Asset Values & Leverage (22 indicators)					
Farm Sector Debt	ERS	Dec 2012	A	DLV	1.12
District Survey 007 - St. Louis	Dist. Surv.	Jun 2012	Q	DLN	1.10
Farm Sector Assets	ERS	Dec 2012	A	DLV	1.09
District Survey 007 - Kansas City	Dist. Surv.	Jun 2002	Q	DLN	1.08
District Survey 007 - Minneapolis	Dist. Surv.	Mar 2001	Q	DLN	1.07
Call Report Performance Metric C002	Call Rpt.	Mar 1984	Q	LV	-1.06
Annual % Change in Land Values - St. Louis	Dist. Surv.	Jun 2013	Q	DLV	1.06
Annual % Change in Land Values - Kansas City	Dist. Surv.	Mar 1991	Q	LV	1.05
Annual % Change in Land Values - Minneapolis	Dist. Surv.	Mar 2002	Q	DLV	1.04
Annual % Change in Land Values - Minneapolis	Dist. Surv.	Mar 2002	Q	DLV	1.04
Annual % Change in Land Values - Minneapolis	Dist. Surv.	Mar 2002	Q	DLV	1.02
Annual % Change in Land Values - Kansas City	Dist. Surv.	Mar 1991	Q	DLV	0.89
Annual % Change in Land Values - Kansas City	Dist. Surv.	Mar 1991	Q	DLV	0.78
Call Report Performance Metric C001	Call Rpt.	Mar 1984	Q	DLN	-0.72
Annual % Change in Land Values - Chicago	Dist. Surv.	Mar 1991	Q	DLV	0.71

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Table A.1 continued

Financial Indicator[1]	Source[2]	Start Date	Freq.	Trans.[3]	Weight[4]
Annual % Change in Land Values - Dallas	Dist. Surv.	Mar 1992	Q	DLV	0.68
Annual % Change in Land Values - Dallas	Dist. Surv.	Mar 1992	Q	DLV	0.63
Annual % Change in Land Values - St. Louis	Dist. Surv.	Jun 2013	Q	DLV	-0.62
Call Report Performance Metric C004	Call Rpt.	Mar 1984	Q	DLN	-0.59
Call Report Performance Metric C003	Call Rpt.	Mar 1984	Q	DLN	0.58
Call Report Performance Metric C005	Call Rpt.	Mar 1984	Q	DLN	-0.56
Annual % Change in Land Values - Dallas	Dist. Surv.	Mar 1992	Q	DLV	0.41

The table lists all 127 indicators used to construct the FFCI, organized by economic category and sorted by absolute weight within each group. Source codes are: Dist. Surv. = Federal Reserve District Agricultural Credit Survey; TERMS = Survey of Terms of Business Lending; CALL = Federal Reserve Call Report; ERS = USDA Economic Research Service; NASS = USDA National Agricultural Statistics Service; FRED = Federal Reserve Economic Data. Frequency codes are: M = monthly, Q = quarterly, A = annual. Transformation codes are: LV = levels, DLV = first difference, DLN = log first difference. Weights are scaled so that absolute values sum to 100 across all indicators.
[1]All indicators are standardized to zero mean and unit variance over the estimation sample prior to factor extraction.
[2]Sources: Call Rpt. = Federal Reserve Call Reports; Dist. Surv. = Federal Reserve District Agricultural Credit Surveys (Chicago, Dallas, Kansas City, Minneapolis, St. Louis); Terms Surv. = USDA/Federal Reserve Survey of Terms of Bank Lending to Farmers; ERS = USDA Economic Research Service Farm Income and Wealth Statistics; NASS = USDA National Agricultural Statistics Service; FRED = Federal Reserve Economic Data.
[3]Transformation codes: LV = Level, DLV = First Difference, DLN = Log First Difference. We apply transformations to achieve stationarity as determined by augmented Dickey-Fuller tests.
[4]Weights are estimated factor loadings scaled so that absolute values sum to 100. Positive weights indicate the series co-moves with improving farm financial conditions (rising net cash income); negative weights indicate inverse co-movement.